Combining farm simulation with frontier efficiency analysis

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Abstract :

The model used, GAMEDE, is a “whole-farm” dynamic model composed of 6 biophysical modules and a management system (Vayssières et al, 2009). This simulation model gives accurate predictions for various sustainability indicators (labor, energy consumption, production, nitrogen leaks to the environment…) to characterize observed or hypothetical farms. As GAMEDE is based on a stock-flow approach, we can monitor the farm stocks (slurry, fodders…) over time. GAMEDE also gives a full description of management operations of the production system. The GAMEDE model is randomly parameterized with the objective to cover the realm of the possible production systems by simulation. Key issues of the methodology are selecting input parameters and defining lower and upper bounds to these parameters. Expert knowledge is very useful to define these bounds. Even though the simulation approach constitutes a relevant tool for describing the production system, it can not provide a full efficiency analysis taking into account multiple input parameters. We suggest combining GAMEDE with “Data Envelopment Analysis” (DEA) to assess the efficiency of a large variety of simulated farms (frontier efficiency analysis). Each farm is characterized by different structural and management inputs parameters, inflows and sustainability indicators (including outflows). The last two types of variables are respectively inputs and outputs used in the DEA model. For inefficient farms, potential efficiency progress is calculated as the distance between these farms and the frontier. The main advantage of our methodology is to benefit of the synergy between simulation and efficiency frontier modelling, as drawback of each method are balanced by the asset of the other method.

1 Introduction

Agricultural systems research has known major improvement thanks to biophysical models. Many models precisely describe the feed/nutrient needs of animals/plants and corresponding productions (e.g. for animals: INRATION; INRA, 2003; e.g. for plants STICS; Brisson et al., 2003). These models give an accurate description of biophysical mechanisms involved in food production, but they fail to describe the functioning of farming systems because they didn’t take into account the farmer’s objective and the constraints farmers face (Sebillote, 1987). Thus, Vayssières et al. (2009a) insist on the necessity to model explicitly the interaction between human activities and biophysical processes to be able to represent realistically farming systems. Additionally, the authors emphasize the limit of models at herd or plot scale and explain that only whole-farm models can assess the impact of a modification (technical or management) on the agricultural production system. GAMEDE is a whole-farm dynamic model. The model has been implemented as a stock-flow model (Vensim® software) to simulate dairy farming systems in La Réunion Island (French overseas department in the Indian Ocean). The model allows to simulate the impact of diverse technical changes and corresponding changes in decision rules on labor, energy consumption, production, nitrogen losses, etc (Vayssières et al., 2009b). Although the accuracy of the GAMEDE model was demonstrated, the simulation approach was limited to the exploration of technical and management changes proposed by technical advisers and farmers. It failed i) to represent the whole realm of feasible farming systems, and ii) to locate the observed and simulated farming systems in this realm of the possible.

Our methodology suggests combining farm simulation with efficiency frontier methods. In this paper, we illustrate this methodology; we use the data envelopment analysis method to assess the efficiency of data sets generated by GAMEDE. DEA method allows us to identify the efficient, and to define the level of inefficiency of every farm deemed as inefficient. It requires defining a technology producing outputs with inputs. The input-output sets are generated with GAMEDE. The major asset of our methodology is to link the efficiency scores with these parameters which are often unknown in classical efficiency analysis of farming systems (Vayssières et al, 2007). Actually, the choice of inputs and outputs is very restrictive in DEA (closely linked to sample size) and interpretation of efficiency score is generally limited. Furthermore, DEA method needs to implement large data sets, to define robust efficiency frontiers and this is very scarcely the case for faming systems.

While optimization and simulation method are often opposed, Jacoby and Loucks (1972) already suggested in 1972 that combination of this two modeling methods may offer a promising assessment approach. In our study case, we analyze whether the combination of the two methods improve both methods with a double hypothesis. Firstly, the frontier efficiency method (based on optimization mathematics) improves the efficiency assessment of the simulation model by a multidimensional (multi-inputs and multi-outputs) analysis and the quantification of the progress margins. Conversely, simulation models as GAMEDE can generate important data sets for optimization method, with the certification that simulated data are coherent in a given agronomic context. In our case study, the objective is not to improve GAMEDE but to progress in farming systems efficiency analysis. We will first introduce both modeling methods (GAMEDE and DEA), then present our results on the case study of dairy farming systems in La Réunion Island. Lastly, the discussion part raises the assets and limits of the proposed methodology. Some methodological improvements are proposed.

2 Methodology

Our method suggests combining simulation modelling and DEA for analyzing efficiency (figure 1). The first part of this methodology description presents the structure of GAMEDE and clarify the various type of data used, while second part briefly describes the data generation process. Lastly, we introduce DEA and the specificity of the linear program used to build the efficiency frontier of dairy farms in La Réunion. The efficiency analysis presented in the lower part of figure 1 will finalize our global efficiency analysis in part 3.

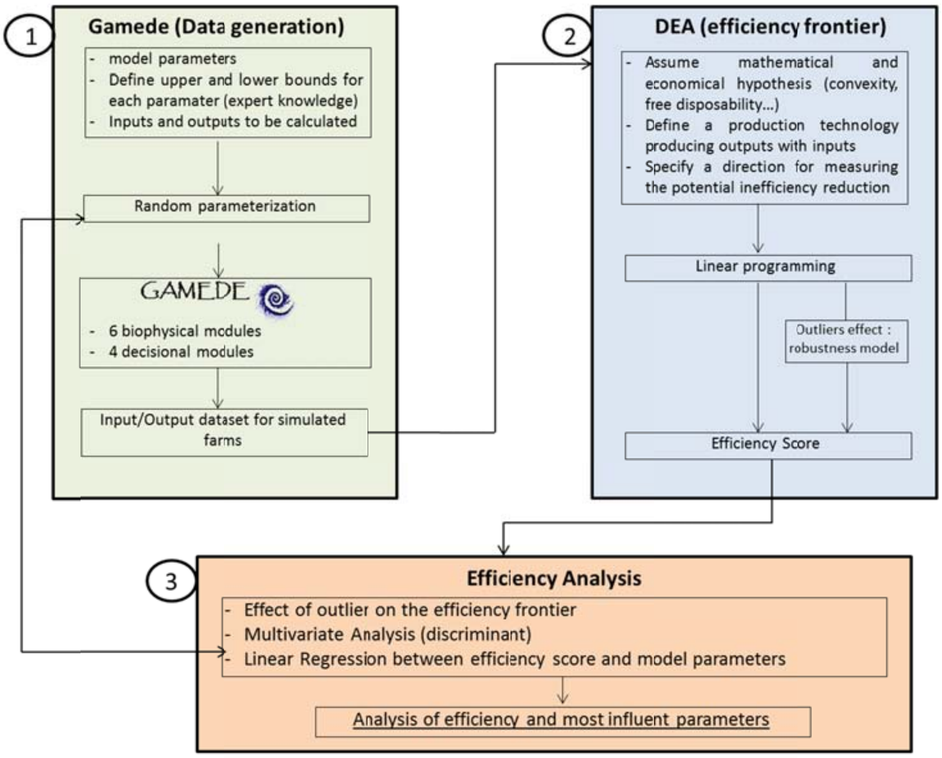

Figure 1: Three-stage methodology for analyzing the efficiency of farming systems

2.1 GAMEDE a whole farm model

GAMEDE is the material support of the simulations related in this paper. GAMEDE is a dynamic simulation model representing the farm agro-ecosystem. It includes more than 22,000 variables that at one moment depend on variables at another moment, representing the changes in the state of the system over time. The model is original in its integration of management and biophysical processes and the representation at daily time steps of interactions occurring between all parts of the agro-ecosystem: the farmer, the livestock, the soil and the forage crops. GAMEDE biophysical modules are based on the recognized mechanistic models MCP (Leteinturier et al., 2004), MOSICAS (Martiné, 2003), INRATION (Faverdin et al., 2007), CNCPS (Fox et al., 2004), SEPATOU (Cros et al., 2003) and GRAZEIN (Delagarde et al., 2004). This integration is described in detail by Vayssières et al. (2009b).

2.1.1 GAMEDE input parameters

Input parameters of GAMEDE relate to farm management, structure, weather, and external resources availability. The management input parameters include the farmer's action plan and his operational decision rules. The fact that management and structure input parameters are detailed allows simulating a wide range of farming systems (Vayssières et al., 2009a and 2011).

2.1.2 The core of the model

The core of the model is based on the causal-chain dependencies between practices and sustainability. First, the management system of GAMEDE simulates technical actions according to the farmer's action plan and operational decision rules, the state of the production and the farm's environment (daily weather and availability of external resources). Secondly, the biophysical system of GAMEDE simulates consequences of these technical actions on main biophysical processes and translates them into biomass flows depending on weather conditions. Biomass flows (expressed in kg of fresh matter: kgFM) are translated into labour (in hours), Nitrogen flows (in kgN), Energy flows (in MJ) and cash flows (in €). Finally, flows are synthesised in sustainability indicators.

2.1.3 GAMEDE outputs

GAMEDE assess the sustainability of the simulated dairy farming systems according to technical, environmental, social and economic indicators.

The technical indicators concern production of forage, milk and meat production. Forage production is the total feed energy harvested by ensiling, cutting and carrying, or direct grazing of forage, on the total utilised agricultural area (in UF year^{-1}). UF is the feed unit defined by the french UF/PDI feeding unit system (Jarrige, 1989) characterising the energy value of a considered feed to allow milk production or weight gain.. Milk and meat productions are expressed in kilogramme of fresh matter (kgFM year^{-1}).

The environmental indicators are focused on N dynamics, non-renewable energy (NRE) consumptions and green house gas (GHG) emissions. The model calculates annual N leaks to the environment and apparent N farm gate balance (Simon and Le Corre, 1992; Nevens et al., 2006). Energy consumptions (in MJ year^{-1}) and GHG emissions (in kgC0_2eq. year^{-1}) considers both direct and indirect NRE consumptions and GEG emissions along the life cycle "from the cradle to the farm-gate" (Bochu, 2007).

The social indicator is the total labour requirement. It is expressed in hours per week to allow comparisons with the statutory working week. Hours of labour are linked to each technical operation to represent direct influence of practice on labour requirement.

The economic indicator is gross margin (in € year^{-1}). This indicator is appropriate for analysing contributions of activities to farm economic viability (De Jager et al., 2001). As the hours of labour are linked to each technical operation, the costs and benefits of each operation are calculated according to management practices and finally summed over time and operations in the annual gross margin.

2.2 Dataset building: the link between the simulation and the optimization models

Variable nomenclature may be confusing because some outputs of the GAMEDE model are used as inputs in the DEA model. Figure 2 summarizes variables used in GAMEDE and DEA to clarify the vocabulary used in this paper.

Before each GAMEDE simulation, some variables (≠ constants) have to be fixed, they are called "input parameters" (defined in § 2.1.). Some of them were selected to be "Explaining variables" in the multivariate analysis (§ 3.3.). They are called "Explaining variables" because they explain efficiency variations. Explaining variables are classified in two types: structural explaining variables (e.g. herd size, agricultural areas) and management explaining variables (e.g. quantity of concentrate feed distributed in the feed ration per cow per day…). The idea was to see if inefficiencies are equally explained by structural and management variables.

Outputs indicators calculated by GAMEDE are used both as Inputs and Outputs variables for the DEA model. "Input variables" are farm consumptions (labor, concentrate, N under the form of mineral fertilizers). "Output variables" are farm productions (milk, meat).

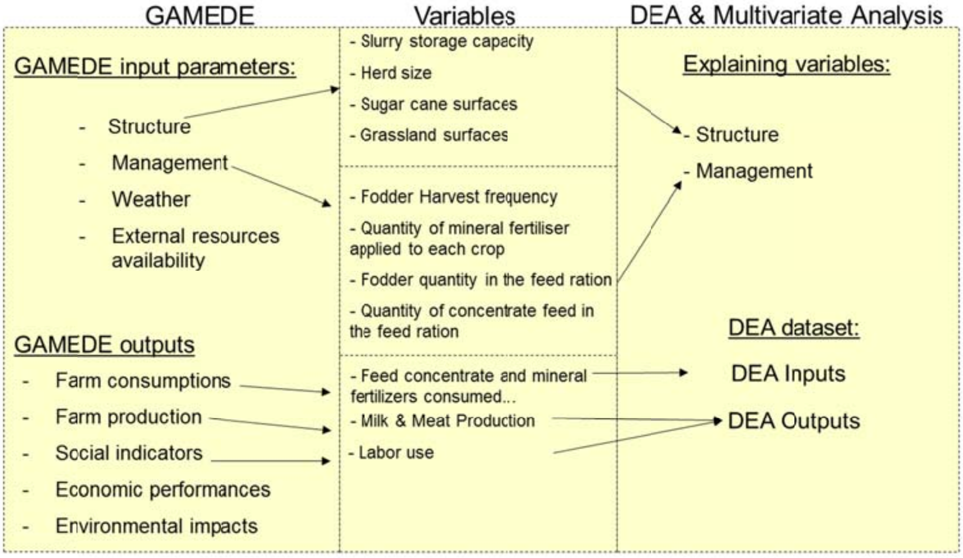

Figure 2: Correspondence between variables calculated by the simulation model (GAMEDE) and used in the optimization model (DEA) and the multivariate analysis

To build large data sets of input/output and explaining variables, GAMEDE was randomly parameterized. The objective was to cover as fully as possible the realm of possible farming systems in the context of La Réunion. Random functions were normal distribution laws centered on mean of values observed during farm survey. Key issues of this data set building are selecting variable input parameters of GAMEDE (= "Explaining variables") and their lower and upper bounds. Lower and upper bounds of distributions were based on observed ranges and expert knowledge from local technical advisers about possible ranges.

2.3 Efficiency analysis with DEA

We use in this paper a non-parametric approach to assess the efficiency of 5000 simulated farms. We choose to implement the Data Envelopment Analysis (DEA) which allows measuring the efficiency of Decision Making Units (DMU) by a mathematical formulation of a production technology characterized by inputs (concentrate feeds, labor…) producing outputs (milk production). This method is first introduced in the operational research by Charnes, Cooper and Rhodes (Charnes et al., 1978). Various papers have implemented this method for the assessment of the efficiency of livestock farming systems (Piot-Lepetit, 1998, Gaspar, 2009…). Thanks to linear programing, the DEA method allows the identification of the efficient farms which minimize their inputs to produce the maximum level of outputs. The efficiency score is the result of a multidimensional analysis (i.e an efficient farm produce more of each outputs with less of each inputs). As we summarize for a 2 dimensions analysis (figure 3), we can see that all the efficient DMU constitute an estimation of the efficiency frontier of the production technology. We implement in this paper a method to assess the robustness of the model and specifically the outlier's impact on the efficiency score. Once this frontier built, every farm is compared to this frontier by the computation of the distance between them and the frontier. As we show it in figure 3, we decided to use a radial output distance. In this condition, the inefficiency score will traduce the potential increase of every outputs, given their inputs level.

In order to formulate our model mathematically, we consider a set of N farms producing O outputs with I inputs, associated with the following index sets: $\aleph = \{1,\dots,N\}$, $\mathrm{O} = \{1,\dots,O\}$ and $\mathrm{I} = \{1,\dots,I\}$. We define by: $\mathbf{y^O} = \left(y^1,\dots,y^O\right) \in R_+^O$ and $\mathbf{x^I} = \left(x^1,\dots,x^I\right) \in R_+^I$, the quantity vectors of outputs and inputs respectively. The production technology is defined by:

$T = \left\{ \left(\mathbf{x}^{\mathbf{I}}, \mathbf{y}^{O} \right) \in R_{+}^{I+O} : \mathbf{x}^{\mathbf{I}} \text{ can produce } \mathbf{y}^{O} \right\}$. By imposing basic axioms on the production technology (particularly free disposability of inputs and outputs, convexity and variable returns to scale) we add a mathematical structure that leads to measure the efficiency of each farm by the following linear program:

$$
\begin{aligned}
& \underset{\mu,h}{\text{Max}} \ \ \text{h} \\
& \sum_{n\in\aleph} \mu_n \mathrm{y}_n^o \geq h \ \mathrm{y}_e^o, \ \forall o \in \mathrm{O} \\
& \sum_{n\in\aleph} \mu_n \mathrm{x}_n^i \leq \mathrm{x}_e^i, \ \forall i \in \mathrm{I} \qquad \text{LP1} \\
& \sum_{n\in\aleph} \mu_n = 1 \\
& \mu_n \geq 0, \ \forall n \in \aleph
\end{aligned}
$$

The evaluated DMU $\left(\mathrm{x}_e^i, \mathrm{y}_e^o \right)$ on the right hand side is compared to a benchmark which is defined by a linear combination of the N DMUs that composed the sample on the left hand side. We expect that the benchmark (projection point of the DMU on the frontier) of the evaluated DMU produces more of each output (first set of constraints) while using less of each input (second set of constraints). We therefore seek the largest proportional increase of the output vector (h) of the evaluated DMU. After solving this model for each DMU in the sample, efficient DMUs will characterize the technology frontier. Inefficient DMUs are situated below the frontier and a measure of their inefficiency is given by the number (h-1), and can be interpreted as the potential increase in outputs.

As the data set used to build the DEA model is based on simulations, there is a risk that some input/output combinations (= theoretical farms) are inconsistent in the context of La Reunion’s Island. In order to estimate the effect of these outliers on the efficiency score, we implement a method based on the outlier detection research of Thanassoulis et al. (2008) and Simar and Wilson (2008). As many methods in outliers detection, the principle used is to implement the DEA on sub-datasets. We implement many DEA models for each sub-dataset of the original dataset, i.e., without the certainty that all the efficient farms are taken into account. Thus, the maximum inefficiency score is observed when the farm is compared to the whole sample (with all the efficient farms) and according to the random selection of the sub-datasets, we will observe lower inefficiency scores as shown in figure 3.

We can see in the left part of the figure 3 that in a model including all farms, the efficiency frontier is built by the farm A, B and C. In the right part, we can see that the exclusion of the farm B has reduced the production set and the inefficiency score. In this paper, we decided to fix the two key parameters of this method, the size of the sub-sample (m=75% of the whole sample) and the number of draws (b=100). We obtained one hundred scores for each farm and the average score could be compared to the model with the complete dataset. The difference between the two scores highlights the influence of the outliers and the reliability of the score observed in the first model.

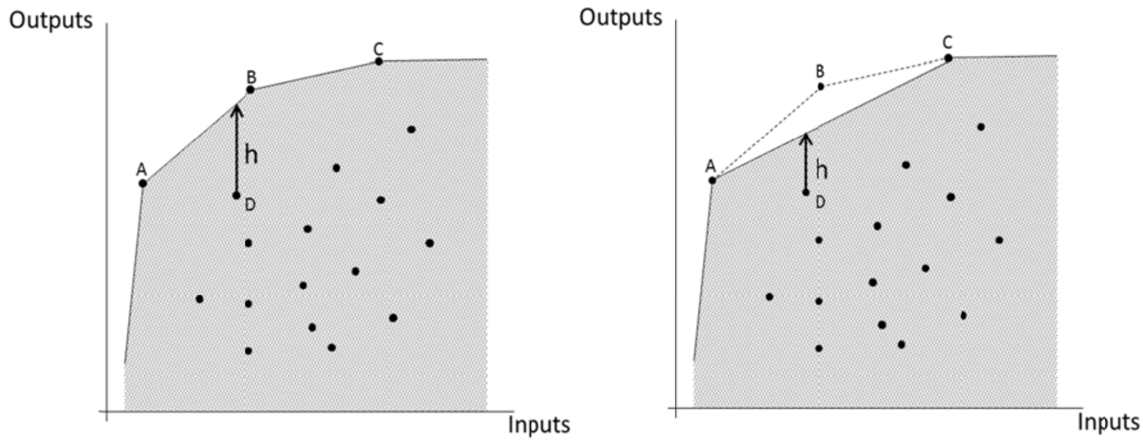

Figure 3: Influence of outliers on the efficiency frontier and the score of farm D for two datasets: the original complete dataset (left) and a sub-dataset (right)

3 Results

The relevant point is here the different methods used and the type of graphic and statistic exploration which can be used in this methodology. We don't explore deeply the meaning of our results in the tropical context of La Réunion but we prefer insisting on the assets of the different results and exploration method.

3.1 Outliers impact on efficiency score and model robustness

As figure 3 expose it, we have describe the production technology in DEA by 2 outputs (meat and milk) produced by three inputs (labor, concentrate feeds and mineral fertilizer). Outliers inefficient farms are easily recognizable as they have very high inefficiency score, but it isn't obvious to identify outliers efficient farms as their score is 1 as the non-outliers efficient farms. We implement the robustness model method in order to quantify the impact of potential outliers in the efficiency frontier. For each farm, we implement a DEA models on 100 random sub-samples of 75 % of the whole sample. Thus, results are compared to the efficiency scores where all farms have been assessed among the 5000 farms of our sample. The results can be synthetized as in table 1. We express in table 1 the mean efficiency score in order to compare it between the two types of modelling. In the non-robust model, we observe a score of 1.80, ie, a potential raise in milk and meat production of 80% of the current level of production. When we use the robust model to reduce the outlier effect, we observe a slight reduction of the score (1.6%). This result doesn't mean that data generation by GAMEDE hasn't generated outliers. Indeed, the score are only impacted by the selection of a sub-sample if some outliers are in the efficiency frontier in the non-robust model (figure 3).

Table 1: Outliers detection and robustness test model.

non robust model	**robust model**			**Outliers impact**
Score (mean)	number of draws (b)	sub-sample size (m)	Score (mean)	Difference (%)
1.80	100	75%	1.77	1.6%

We can conclude that outliers generated by GAMEDE are inefficient. It is coherent with the very important level of inefficiency observed.. We can also argue that GAMEDE has many parameter controls and efficiency frontier must be limited by the biophysical possibility production. In other words, the random choice of parameters in the data generation process in GAMEDE generate outliers but always very inefficient, and as a consequence doesn't affect the structure of the efficiency frontier.

3.2 Efficiency characterization (multivariate analysis and linear regression)

Multiple discriminant analysis (MDA) is a common descriptive method based on parametrical models. The main goal of this statistic analysis is to characterize a data set by different classes and support an optimal graphic representation of the class diversity. Therefore, the method maximizes the inter-group variance while intra-group variance is minimized. In order to implement this method without the influence of the inefficient outliers (with score up to 1267), we focus this analysis on the efficiency score between 1 and 2. Five groups of farms are made in this efficiency score class:

- **1** : Efficiency score : 1 (efficient farm)
- **2** : 0 à 10% of potential improvement (score between 1 and 1.1)
- **3** : 10 à 20% of potential improvement (score between 1.1 and 1.2)
- **4** : 20 à 50% of potential improvement (score between 1.2 and 1.5)
- **5** : 50 à 100% of potential improvement (score between 1.5 and 2)

The multiple discriminant analysis allows characterizing this group according to farm structure and practices (GAMEDE inputs parameters). Indeed, this method allows us to define a whole set of parameter specific to each dataset of inputs/outputs.

MDA emphasizes a gradient between the different groups. The lower score (efficient farms) are correlated to the important herd and high level of concentrate feed. Conversely, the higher score seems to be linked with large grassland surfaces, which need important use of fertilizers and labor for harvest activities. Indicators generated by GAMEDE point out a correlation between gross margin and the efficient farms.

We made a linear regression of the efficiency score in order to see the most influential structural and management parameters in GAMEDE. We observe similar results as in the Multifactorial discriminant analysis. Herd size and quantities of concentrate feed used to feed cows are linked to the most efficient farms while grassland surfaces are typical to inefficient farms.

Linear regression allows us to identify influential parameters on the efficiency score (concentrate feeds for dairy cows, herd size, grassland surfaces). Moreover, linear regression provides indicators which give an intuitive interpretation of the influential parameters. For example, linear regression demonstrate that an increase of herd from 80 to 110 induce a reduction of inefficiency score of 0.073. Similarly, if the farmer increase concentrate feeds from 8.5 to 13.5 ($Kg.cow^{-1}.day^{-1}$), he will reduce his inefficiency by 0.0141.

4 Concluding remarks on the proposed methodology

As figure 1 exposed it, our methodology of efficiency assessment benefits of both simulation and optimization modelling and drawback of each method are compensate by the asset of the other method. GAMEDE and Data Envelopment Analysis appear to be very complementary, as simulation farm models allows generating consistent farms datasets in a given agronomic context, and frontier efficiency methods allow identifying efficient farms and level of inefficiency of non-efficient farms.

Empirically, our application on the dairy farming systems in La Réunion highlights specificity of this insular livestock sector: a land limited and mountainous territory. Statistical analysis emphasizes that efficient farms own important herds and use significant quantities of concentrate feeds for cattle feeding. Moreover, parameters which appear to be negatively linked to efficiency are all relative to grassland management. In Réunion's island, dairy farms are essentially located in the upper part of the island, as low littoral lands are reserved to sugar cane. Thus, lands available for dairy production are generally steep and pebbly. In these conditions, forage production is costly and appears inefficient with reference to the concentrate feed option. Nevertheless, in this study, we only considered classical milk and meat production indicators (good outputs) and we can assume that characteristics of efficient farms would be very different if we would have integrated direct and indirect greenhouse gases emissions (GHG) in the frontier analysis (as a bad output). In fact, concentrate feed consumption is a strong contributor to indirect GHG emissions in the life cycle analysis (LCA) of dairy farms (Vayssières et al., 2010). New methods in efficiency frontier analysis allow considering undesirable outputs as GHG emissions or nitrogen leaks to the environment (Berre et al., 2011).

The combination of simulation and optimization models to analyze the efficiency of farming systems is a new methodology. The main risk we identified in this methodology is the inconsistency of some simulated farming systems and then of the corresponding input-ouput points used in DEA. As the parameter selection is independent of the other parameter value, we understand that there is a risk that many simulated combinations may be not realistic, in particular if farm models are pure biophysical models. The fact that GAMEDE represents accurately the most influent biophysical and management processes on farming systems functioning and performances, guaranties the coherence of input-output datasets. For instance quantity of concentrate feeds consumed by cows on a daily basis are limited by intake capacity of animals (a biophysical rule) and quantity of concentrate feeds bought (an input) do not exceed needs defined by the feed ration (a management parameter). Despite the existence of a decision system, we have noted that the random selection of parameter value generated some outliers. As we demonstrated in part 3.1, we noted that outliers correspond to very inefficient farms and do not impact the efficiency frontier structure. The robustness of the model implemented confirms this assumption. This assumption has to be explored for datasets generated by pure biophysical farm models (e.g. Nuances-FarmSim, Van Vijk et al., 2009) where some efficient farms will probably be outliers.

Finally, our methodology suggests a new way to analyze the efficiency of farming systems. Our three-stage efficiency analysis methodology confirms that simulation models and efficiency frontiers are complementary. Simulation models built on deep knowledge of main biophysical and management processes involved in farm functioning allows to generate the large dataset needed to build robust efficiency frontiers. Conversely, frontier efficiency analysis complete the classical “what if?” approach largely associated to simulation models by a better representation of the realm of possible farming systems. This is a strong benefit of coupling the two methods. During data set generation, upper and lower bound fixed for each parameter of the simulation model is a key methodological point that have to be addressed carefully. The bounds are conditioning the consistency of the simulated farms in a given agricultural context and then the validity of the input/output data set and the corresponding frontier. We recommend using local expert knowledge and observed ranges (in survey) to define these bounds. Regarding last prospective reports on the food sector (MEA, 2005; Chaumet et al., 2009; FAO, 2011) and their recommendations to focus on efficiency to ensure food security with limited impact on the environment, we consider that the combination of farm simulation models and frontier efficiency analysis is a promising methodology.

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